Int. Fin. Markets, Inst. and Money 29 (2014) 1–12

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Macroeconomic impacts of oil prices and underlying financial shocks

Wang Chen [a], Shigeyuki Hamori [b], Takuji Kinkyo [b,*]

[a] Graduate School of Economics, Kobe University, 2-1, Rokkodai, Nada-ku, Kobe 657-8501, Japan
[b] Faculty of Economics, Kobe University, 2-1, Rokkodai, Nada-Ku, Kobe 657-8501, Japan

ARTICLE INFO

Article history:
Received 20 August 2013
Accepted 27 November 2013
Available online 6 December 2013

Keywords:
Oil price
Financial shock
Financialization of commodity markets
Kilian's two-step approach

ABSTRACT

We extend Kilian's (2009) framework to identify an exogenous shock arising from changes in financial market conditions and examine the consequent macroeconomic impacts of oil price changes. We find that a financial shock is a key determinant of oil prices and its macroeconomic impact is as important as the impact of other underlying shocks. The results indicate that policymakers must explicitly consider changes in financial market conditions when analyzing the impacts of oil shocks. Further, a stabilisation policy must be forward-looking and tailored to underlying causes because different shocks have different impacts at different time horizons.

1. Introduction

Large fluctuations in oil prices and their high volatility have long been sources of instability in the global economy. In particular, the sharp rise in oil prices during the commodity boom that started in the early 2000s posed serious challenges to macroeconomic management in both developed and developing countries. Against this background, a large body of literature has empirically examined the underlying causes of oil price fluctuations and their macroeconomic impacts. Early research mainly focuses on the relationships between oil prices and economic activity (see, for example, Hamilton, 1983; Hooker, 1996), finding a strong negative relation between rising oil prices and GDP growth

* Corresponding author. Tel.: +81 78 803 6828.
E-mail addresses: tinou3776@yahoo.co.jp (W. Chen), hamori@econ.kobe-u.ac.jp (S. Hamori), kinkyo@econ.kobe-u.ac.jp (T. Kinkyo).

1042-4431/$ – see front matter
http://dx.doi.org/10.1016/j.intfin.2013.11.006

in many countries. Previous studies also suggest a positive association between rising oil prices and inflationary pressures on the economy (see, for example, Cunado and Perez de Gracia, 2005).

Further, while a growing body of literature examines the effect of oil prices on the stock market, there is no robust consensus about the effect of oil price shocks on stock market returns. Ciner (2001) finds that a statistically significant relationship exists between oil price futures and real stock returns, but that the correlation is non-linear. Similarly, Aloui et al. (2008) find that changes in oil prices significantly increase the volatility of stock market returns in six developed countries. By contrast, Jammazi and Aloui (2010) show that oil price shocks do not affect stock market returns during recession phases.[1]

Recent studies have shown that the effects of oil price shocks on stock markets depend on whether the country is an oil importer or an oil exporter. For example, Park and Ratti (2008) show that oil price shocks account for a statistically significant proportion of the volatility in real stock returns. Moreover, they find that the increased volatility of oil prices significantly depresses real stock returns in many European oil-importing countries. Arouri and Rault (2012), on the other hand, report that oil price increases positively influence stock prices in Gulf Cooperation Council countries, except in Saudi Arabia.

Despite the accumulation of empirical evidence, however, two major deficiencies are evident in the traditional approach to modelling oil price shocks frequently used in the literature. First, although reverse causality may run from real economic activities to oil prices, oil price shocks are assumed to be exogenous. Second, the recent literature presents evidence that the relation between oil prices and stock prices depends on the origin and nature of oil price shocks (see, for example, Ciner, 2013; Degiannakis et al., 2013). These results indicate that the macroeconomic impacts of oil price shocks could depend on the underlying causes, which has not been fully taken into account in previous analyses.

Kilian (2009) proposes a two-step approach to analyzing the macroeconomic impacts of oil price shocks in order to overcome these shortcomings. In the first step, a vector autoregression (VAR) that includes oil production, global economic activity, and oil prices as endogenous variables is estimated in order to identify three types of structural shocks that underlie oil price changes: an oil supply shock, an aggregate demand shock, and an oil market-specific demand shock that reflects an unexpected change in precautionary oil demand. In the second step, ordinary least squares (OLS) regressions are estimated to evaluate the impact of the identified structural shocks on the macroeconomic indicators. Kilian (2009) adopts this framework to demonstrate that US macroeconomic indicators respond differently to oil price shocks depending on the types of underlying shocks.

Kilian's (2009) two-step approach has been employed by recent studies of how oil price shocks influence real economic activity and stock markets. For instance, it has been shown that the consideration of the origins of oil price shocks is crucial, since different shocks in the oil market have diverse effects on real activity and stock markets (see, among others, Kilian and Park, 2009; Apergis and Miller, 2009; Yoshizaki and Hamori, 2013). However, to the best of our knowledge, no authors have yet attempted to extend Kilian's (2009) framework in order to identify an exogenous shock that arises from unexpected changes in financial market conditions and examine the consequent macroeconomic impacts of oil price changes. This extension must be meaningful because there is emerging evidence of the so-called financialization of commodity markets, a phenomenon characterised by a high degree of price correlation among a broad set of commodities as well as between commodities and financial assets, presumably due to the greater participation of financial investors in commodity markets (Henderson et al., 2012; Nissanke, 2012; Singelton, 2012; Tang and Xiong, 2012; Buyuksahin and Robe, 2012; Morana, 2013; Basak and Pavlova, 2013). A consequence of the financialization process is that commodity prices such as oil prices are determined not only by their supply and demand but also by the financial market conditions that affect financial investment.

The financial collapse of 2008 has sparked renewed interest in the accurate measurement of financial shocks to the real economy. In this context, many researchers have developed methods for constructing financial condition indexes, which contain information on financial variables selected

[1] Similar findings are reported in Huang et al. (1996) and Cong et al. (2008).

not only from stock markets but also from bond markets and the banking system. This approach is necessary because individual indicators (e.g., those only derived from stock markets) may provide ambiguous signals if financial conditions do not change simultaneously or uniformly. In this paper, we use the Kansas City Financial Stress Index (KCFSI) developed by the Federal Reserve Bank of Kansas City as a proxy for global financial market conditions. The KCFSI is a composite index designed to measure the level of stress in US financial markets. It includes 11 financial variables such as TED spread, treasury and corporate bond spreads, and the volatility of stock prices.[2] By assuming that US financial market conditions reflect, to a significant degree, the overall conditions in global financial markets, the KCFSI provides a reasonable measure of stress in global financial markets. An increase in financial stress will be associated with higher funding costs and greater economic uncertainty, resulting in declining real economic activity. Moreover, an increased financial stress will render financial investors more risk averse, which will discourage investment in asset markets, resulting in falling asset prices, including oil prices (Hakkio and Keeton, 2009; Davig and Hakkio, 2010).

The remainder of the paper is organised as follows: Section 2 identifies those structural shocks that underlie oil price changes by estimating a structural VAR; Section 3 examines the impact of the identified structural shocks on the macroeconomic indicators in five major industrial countries, namely France, Germany, Japan, the UK, and the USA; and Section 4 presents the summary and conclusions.

2. Structural shocks that underlie oil price changes

2.1. Structural VAR model

In this section, we identify the structural shocks that underlie oil price changes by estimating a VAR model. The structural shocks to be identified include an oil supply shock, an aggregate demand shock, an oil-specific demand shock, and a financial shock. The structural representation of the VAR model is as follows:

$$A_0 y_t = \alpha + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is a (4×1) vector that contains global crude oil production (COP), global real economic activity (REA), real oil prices (ROP), and the KCFSI, A_0 denotes a contemporaneous coefficient matrix, α denotes a vector of constant terms, and ε_t denotes a vector of serially and mutually uncorrelated structural shocks. Under the appropriate identifying restrictions, structural shocks can be recovered from the estimated reduced-form errors by using the following relationship:

$$e_t = A_0^{-1} \varepsilon_t \tag{2}$$

where e_t denotes the reduced-form errors.

COP is measured by using the total world crude oil production provided by the *Oil and Gas Journal*. REA is measured by using the index developed by Kilian (2009).[3] This index is constructed by using single-voyage freight rates for bulk dry commodity cargoes. It is then deflated by the US consumer price index and linearly de-trended in order to remove the effects of technological advances in shipbuilding and other long-term trends in demand for sea transport. ROP is measured by using the US West Texas Intermediate price deflated by the US producer price index. The data source is the IMF's International Financial Statistics. Finally, as discussed in Section 1, we use the KCFSI as a proxy for global financial market conditions. The KCFSI is normalised to have a mean value of zero and a standard deviation of

[2] The KCFSI includes the following 11 variables: 3-month TED spread, 2-year swap spread, off-the-run/on-the-run 10-year treasury spread, Aaa/10-year treasury spread, Baa/Aaa spread, high-yield bond/Baa spread, consumer ABS/5-year treasury spread, the correlation between stock and treasury returns, the implied volatility of overall stock prices, the idiosyncratic volatility of bank stock prices, and the cross-sectional dispersion of bank stock returns. See Hakkio and Keeton (2009) for details on the KCFSI. The data are available on a monthly basis from the early 1990s until recently and they can be downloaded at http://www.kc.frb.org/research/indicatorsdata/kcfsi/.

[3] The data for the index are available at http://www-personal.umich.edu/~lkilian/.

one. A positive (negative) value indicates that financial stress is above (below) the long-run average, which would discourage (encourage) investment in asset markets, including oil markets.

A VAR model is estimated by using the log-difference of COP and ROP and the levels of the KCFSI and REA divided by 100.[4] The sample period runs from January 1991 to December 2012. In line with the approach taken by Kilian (2009), a VAR is estimated by using 24 lags of each variable to allow for the potentially long-run effects of structural oil price shocks on the economy.[5] We then identify structural shocks by using the Choleski decomposition, with the order being COP, REA, ROP, and the KCFSI. This order determines the exogeneity of the variables; a shock on a particular variable has a contemporaneous effect on the variables ordered after that particular variable but not before it. Following Kilian (2009), COP is assumed to be least responsive presumably due to the high adjustment costs of oil production, followed by REA and ROP. By adopting this ordering, we assume that the oil supply shock, aggregate demand shock, and oil-specific demand shock can be captured by using the structural shock to COP, REA, and ROP, respectively.

The KCFSI, which will capture the financial shock, is placed after ROP based on the assumption that oil prices have contemporaneous effects on financial markets but not vice versa. This assumption is in line with the existing literature. For example, Kilian and Park (2009) employ a VAR model and investigate stock market fluctuations associated with oil price shocks with the ordering of oil production, real economic activity, real oil prices, and real stock returns. Basher et al. (2012) estimate a structural VAR model in order to investigate the dynamic relationship between oil production, real economic activity, oil prices, TED spread, exchange rates, and emerging market stock prices, imposing the restriction that TED spread is allowed to react contemporaneously to oil prices, but not vice versa. Kang and Ratti (2013) examine the relationship between oil shocks, economic policy uncertainty, and stock prices by estimating a structural VAR with the ordering of oil production, real economic activity, real oil prices, a proxy variable for economic policy uncertainty, and real stock returns. Kilian and Vega (2011) show that oil prices do not respond contemporaneously to domestic macroeconomic news, which is consistent with the commonly used identifying assumption that oil price shocks are predetermined with respect to domestic macroeconomic aggregates. Hence, the reduced-form VAR is obtained by multiplying both sides of Eq. (1) by A_0^{-1}, which has the following recursive structure:

$$\begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{pmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \times \begin{pmatrix} \varepsilon_{\text{oil supply shock}} \\ \varepsilon_{\text{aggregate demand shock}} \\ \varepsilon_{\text{oil-specific demand shock}} \\ \varepsilon_{\text{financial shock}} \end{pmatrix} \tag{3}$$

2.2. *Impulse response to structural shocks*

To illustrate the relative importance of the identified structural shocks as sources of oil price changes, the cumulative impulse responses of ROP and other variables to a one-standard deviation shock are shown in Fig. 1. The dotted lines represent two-standard error bands.

Fig. 1 highlights that the effect of an unexpected increase in oil supply on ROP is small and statistically insignificant. By contrast, an unexpected increase in aggregate demand causes a statistically significant increase in ROP, which peaks after approximately six months. An unexpected increase in oil market-specific demand has an immediate and relatively large positive impact on ROP, which is persistent and statistically significant. These results are broadly consistent with those of Kilian (2009).

[4] According to the augmented Dickey–Fuller test, all transformed variables are stationary at the 5% significance level except the transformed REA. However, the DF-GLS test indicates that the transformed REA is stationary at the 5% significance level. We therefore assume that all transformed variables are stationary in the analysis presented herein. We also checked that the stability condition of a VAR, which requires all characteristic roots to lie within the unit circle, is met.

[5] The Akaike Information Criterion (AIC) indicates a lag length of 6. The estimation results based on 6 lags are similar to those based on 24 lags.

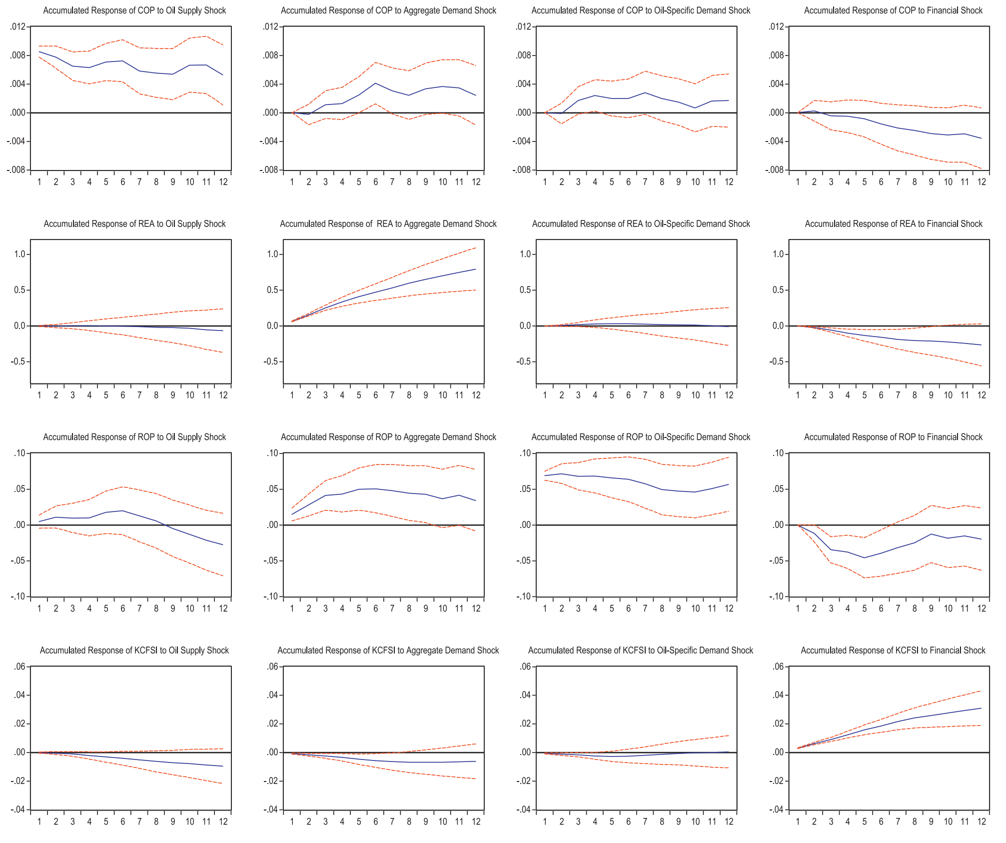

Fig. 1. Cumulated responses to a one S.D. shock with two-standard error confidence bands. Note: the dotted lines represent two-standard error bands.

The impulse response of ROP to the financial shock is of particular interest herein. The figure indicates that ROP declines in the face of a positive financial shock, which implies an increase in financial stress. Such an unexpected worsening of financial conditions causes a statistically significant decline in ROP, which bottoms out after approximately five months. We also find that a positive financial shock depresses real economic activity.[6]

The findings presented in this section indicate that a financial shock is an important determinant of oil prices. This result seems to lend some support to the view that oil markets have become financialized in the sense that oil prices are significantly driven by changes in financial market conditions that affect financial investment.

2.3. Variance decomposition

In this section, we investigate the contribution of different structural shocks to the fluctuations of the variables in the VAR by estimating the forecast error variance decomposition. Table 1 shows the

[6] This result is consistent with the findings of Basher et al. (2012). They show that a rise in financial stress, measured by an increase in TED spread, tends to depress real oil prices, real economic activity, and emerging stock market prices.

Table 1
Forecast error variance decomposition.

Period	Oil supply shock	Aggregate demand shock	Oil-specific demand shock	Financial shock
Variance decomposition of ROP				
1	0.417	4.253	95.330	0.000
	(1.015)	(2.697)	(2.816)	(0.000)
2	1.161	7.290	88.945	2.604
	(1.793)	(3.779)	(4.510)	(2.479)
3	1.053	9.281	78.600	11.066
	(1.776)	(4.269)	(5.828)	(4.788)
4	1.052	9.338	78.423	11.187
	(1.957)	(4.322)	(5.899)	(4.812)
5	1.958	9.809	76.301	11.931
	(2.505)	(4.419)	(6.031)	(4.871)
6	2.016	9.733	75.731	12.520
	(2.649)	(4.399)	(5.954)	(4.849)
7	2.754	9.595	74.515	13.136
	(2.987)	(4.326)	(5.942)	(4.915)
8	3.427	9.535	73.584	13.454
	(3.312)	(4.325)	(6.039)	(4.938)
9	4.907	9.199	70.757	15.136
	(3.826)	(4.320)	(6.168)	(5.271)
10	5.718	9.550	69.417	15.314
	(4.096)	(4.429)	(6.082)	(5.057)
11	6.634	9.678	68.511	15.176
	(4.319)	(4.378)	(6.032)	(5.023)
12	7.023	10.204	67.638	15.136
	(4.391)	(4.452)	(5.998)	(4.909)
Variance decomposition of KCFSI				
1	0.142	5.337	3.354	91.167
	(0.778)	(2.808)	(2.293)	(3.570)
2	0.530	6.657	2.761	90.052
	(1.468)	(3.801)	(2.553)	(4.658)
3	1.491	6.660	2.869	88.980
	(2.465)	(4.475)	(3.161)	(5.722)
4	3.645	6.523	3.183	86.649
	(3.764)	(4.979)	(3.685)	(6.653)
5	4.558	8.026	2.663	84.753
	(4.599)	(5.995)	(3.659)	(7.660)
6	5.200	7.984	2.349	84.467
	(5.398)	(6.485)	(3.328)	(8.310)
7	6.056	7.544	2.409	83.990
	(6.178)	(6.598)	(3.078)	(8.811)
8	6.682	7.026	2.692	83.600
	(6.880)	(6.615)	(3.282)	(9.307)
9	7.157	6.737	3.113	82.993
	(7.485)	(6.638)	(3.856)	(9.830)
10	7.388	6.483	3.117	83.012
	(7.894)	(6.516)	(4.212)	(10.128)
11	8.095	6.297	3.052	82.556
	(8.456)	(6.394)	(4.482)	(10.459)
12	8.457	6.134	3.129	82.280
	(8.803)	(6.371)	(4.828)	(10.765)

Note: the values in parentheses represent the *t*-statistics when coefficients' standard errors were generated from Monte-Carlo simulations with 1000 replications.

share of the fluctuations in ROP and the KCFSI caused by its own shocks (the oil-specific demand shock and financial shock, respectively) compared with the shocks to the other variables.

A major share of ROP fluctuations is accounted for by its own shock (i.e., oil-specific demand shock), although the contribution of this shock declines over time. We note that the financial shock accounts for a larger share of ROP fluctuations than the aggregate demand shock after 3 months and thereafter.

The financial shock explains approximately 15% of ROP fluctuations, while the aggregate demand shock accounts for just 10% after 12 months. On the other hand, the oil supply shock accounts for the lowest share of ROP fluctuations (7% after 12 months), which could be seen as an indication of its low explanatory power. These results are broadly similar to the findings for the impulse responses analysis presented above.

The fluctuations in the KCFSI are mostly caused by its own shock (i.e., financial shock) at all time horizons. The combined contribution of the other shocks to KCFSI fluctuations accounts for approximately 18% after 12 months. Interestingly, we find that the share of KCFSI fluctuations caused by other shocks changes over time. For example, the aggregate demand shock accounts for a larger share of KCFSI fluctuations than the oil supply shock until 8 months. However, the oil supply shock accounts for a larger share of KCFSI fluctuations than the aggregate demand shock thereafter. We also find that the oil-specific demand shock accounts for approximately 2–3% of KCFSI fluctuations throughout the study period, which is constantly lower than the demand shock.

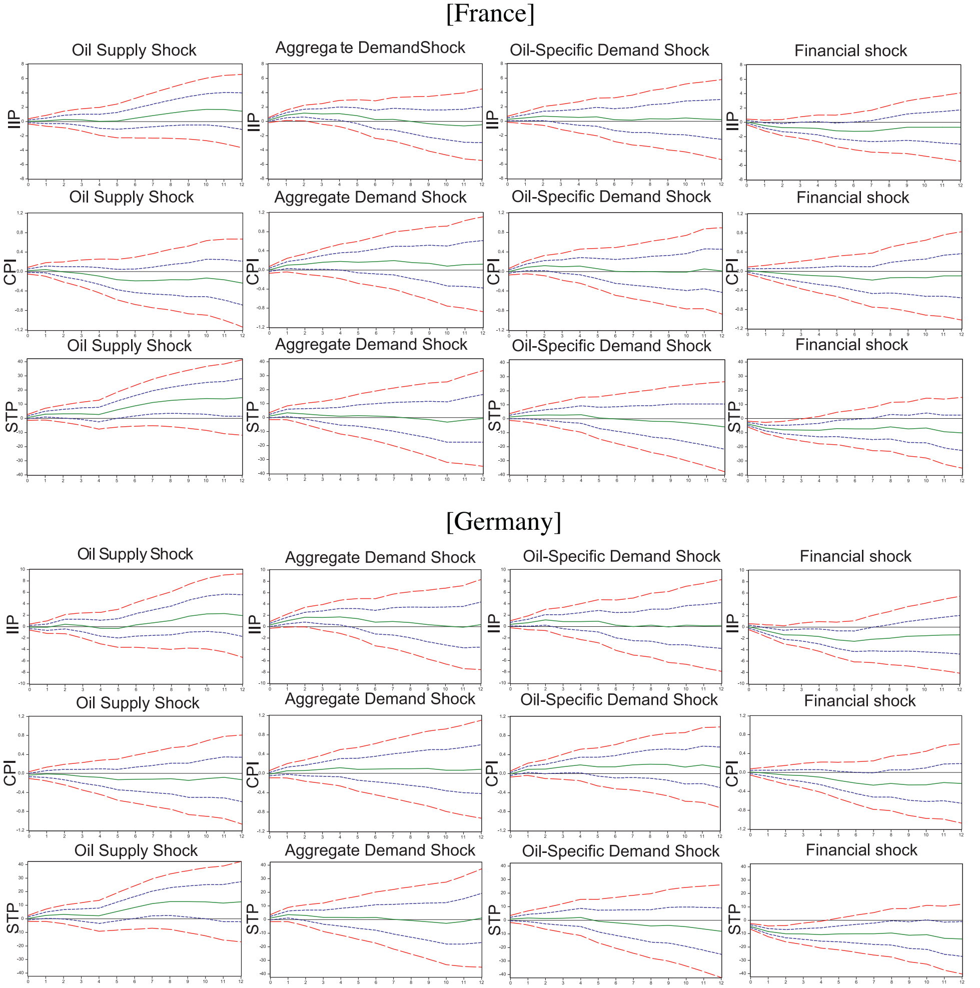

Fig. 2. Cumulative responses of the macroeconomic indicators to the structural shocks. Note: the dotted and dashed lines represent one-standard and two-standard error bands, respectively.

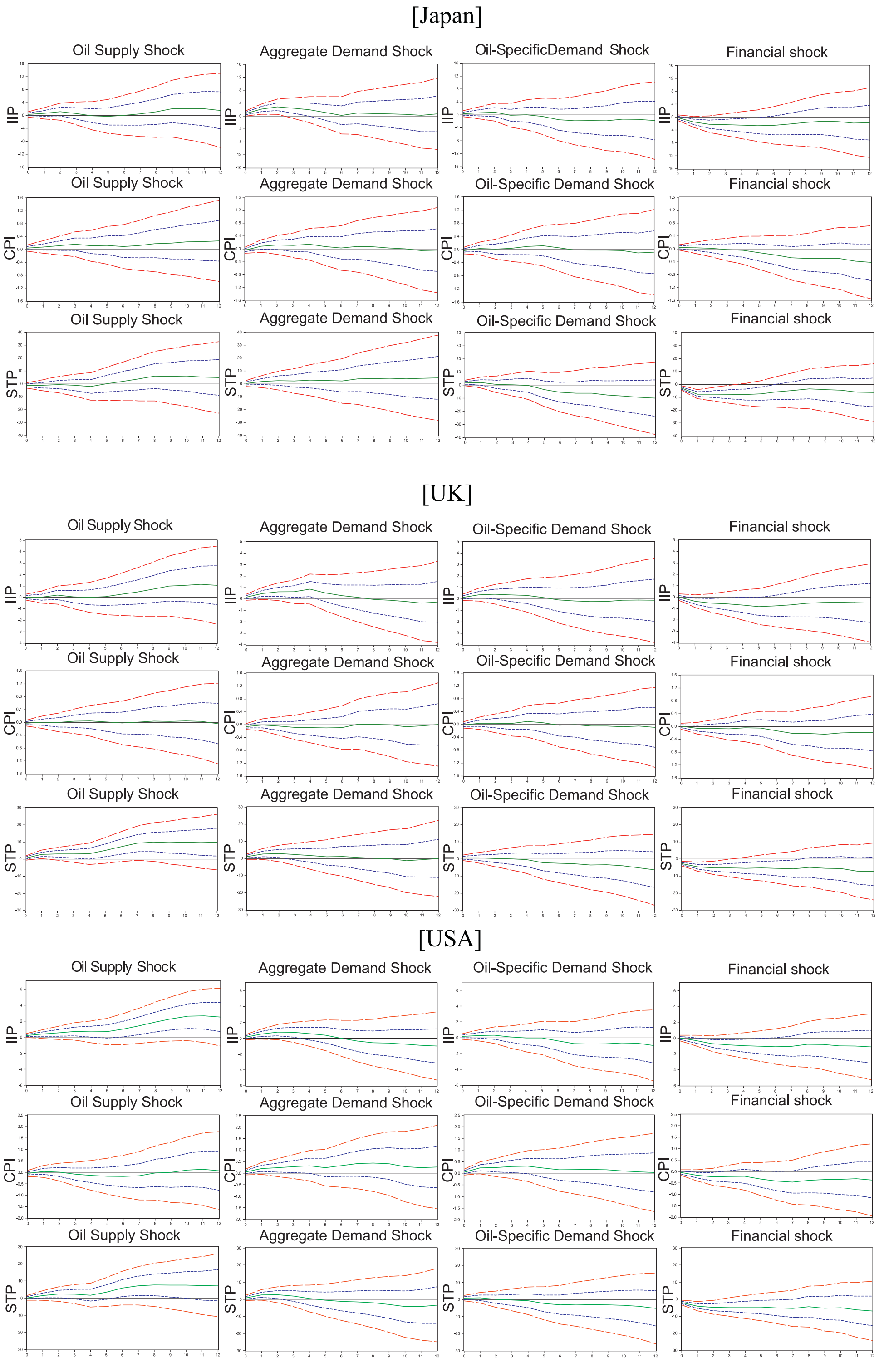

Fig. 2. (*Continued*).

3. Macroeconomic impacts of structural shocks

3.1. OLS regressions

In this section, we examine the impact of the identified structural shocks on the macroeconomic indicators by estimating OLS regressions.[7] The explanatory variables are the four structural shocks identified in Section 2, which are standardised by subtracting the mean and dividing by the standard deviation. The dependent variables are the following three macroeconomic indicators: the index of industrial production (IIP), consumer price index (CPI), and stock price index (STP).[8] An OLS regression is estimated for each of these macroeconomic indicators by using quarterly data from 1993Q1 to 2012Q4.[9] The sample includes data for France, Germany, Japan, the UK, and the USA. Following Kilian (2009), measures of quarterly shocks are constructed by averaging monthly shocks for each quarter:

$$\hat{\vartheta}_{jt} = \frac{1}{3}\sum_{i=1}^{3}\hat{\varepsilon}_{j,t,i}, \quad j = 1, 2, 3, 4 \tag{4}$$

where $\hat{\vartheta}_{jt}$ denotes the jth structural shock in the tth quarter and $\hat{\varepsilon}_{j,t,i}$ denotes the estimated jth structural shock in the ith month of the tth quarter.

The effects of the estimated structural shocks on the macroeconomic indicators are examined by estimating the following regressions:

$$\begin{aligned}
\Delta IIP_t &= \alpha_j + \sum_{i=0}^{12}\varphi_{ji}\hat{\vartheta}_{jt-i} + r_{jt}, \quad j = 1, 2, 3, 4 \\
\Delta CPI_t &= \beta_j + \sum_{i=0}^{12}\tau_{ji}\hat{\vartheta}_{jt-i} + \nu_{jt}, \quad j = 1, 2, 3, 4 \\
\Delta STP_t &= \gamma_j + \sum_{i=0}^{12}\omega_{ji}\hat{\vartheta}_{jt-i} + s_{jt}, \quad j = 1, 2, 3, 4
\end{aligned} \tag{5}$$

where Δ denotes the percentage change in the relevant variables, α_j, β_j, and γ_j are constant terms, φ_{ji}, τ_{ji}, and ω_{jt} are the impulse response coefficients at horizon i, and r_{jt}, ν_{jt}, and s_{jt} are error terms. The maximum lag is determined by the maximum horizon of the impulse function, which is set to 12 quarters. Since there is a potential problem of serial correlation in the error terms, the block bootstrap method is used to infer the estimated coefficients. Specifically, we use an overlapping moving block bootstrap method with block size 4 and 20,000 bootstrap replications.[10]

3.2. Estimation results

The cumulative impulse responses of the macroeconomic variables to the structural shocks are shown in Fig. 2. The dotted and dashed lines represent one-standard error and two-standard error bands, respectively. In the discussion below, the statistical significance is determined based on one-standard error bands.

A positive oil supply shock (an unexpected increase in oil supply) causes a sustained and statistically significant increase in IIP only in the USA. The effects of an oil supply shock on CPI are statistically

[7] Alternatively, we can use a finite distributed lag model such as an Almon lag model in order to avoid potential multicollinearity among the explanatory variables in an OLS regression. However, the variance inflation factor is less than two in all the estimated OLS regressions, indicating that the degree of multicollinearity is low. We therefore use the results of OLS regressions in the presented analysis.

[8] All the data for IIP and CPI are seasonally adjusted. STP is converted into the real value by deflating by using CPI. The data source is the IMF's International Financial Statistics.

[9] The start date of 1993 reflects the need to accommodate lags in the VAR.

[10] See MacKinnon (2006) for a survey of bootstrapping methods.

insignificant in all countries.[11] By contrast, a positive oil supply shock leads to a statistically significant increase in STP in all countries except Japan. The corresponding responses in STP are statistically significant for all or almost all horizons in France and the UK. Likewise, the corresponding responses in STP are positive in Germany and the USA, although they are statistically significant only after the second year.

A positive aggregate demand shock (an unexpected increase in aggregate demand) causes an increase in IIP in all countries in the first year. In particular, the positive response of IIP is highly statistically significant based on two-standard error bands in France and Japan. However, these cumulative responses peak in the second half of the first year, followed by a statistically insignificant decline towards or below the initial level in the third year. The result is fully consistent with one of the key findings of Kilian (2009). The corresponding response of STP follows a similar pattern, except in Japan. These results indicate that the initial direct effect of the aggregate demand shock on IIP and STP wears off over time, which is offset almost fully or more than fully by the shock's lagged indirect effect through higher oil prices due to increased aggregate demand. Moreover, a positive aggregate demand shock causes a statistically significant increase in CPI in France and the USA in the first year.

A positive oil market-specific demand shock (an unexpected increase in precautionary oil demand) causes a temporary and statistically significant increase in IIP only in European countries. In the USA and Japan, the corresponding responses are statistically insignificant. A positive oil market-specific demand shock causes a statistically significant increase in CPI in France, Germany, and the USA. By contrast, the shock does not cause a statistically significant increase in STP in all countries. This result is consistent with that of Degiannakis et al. (2013), which find that the precautionary demand oil shock has no significant impact on the stock returns of European industrial sectors.

The impulse responses of the macroeconomic indicators to financial shocks are of particular interest in this paper. As expected, a positive financial shock (an unexpected increase in the KCFSI, implying increased stress in financial markets) causes a highly statistically significant decline in IIP in all countries. This finding indicates that as financial stress rises, increased funding costs and greater uncertainty depress real economic activity.[12] These cumulative responses of IIP bottom out after the second year, followed by a statistically insignificant increase. However, the response remains negative in the following period. A similar response pattern is observed for STP. These results indicate that, unlike the aggregate demand shock, the initial impact of the financial shock is sustained presumably due to the shock's weaker offsetting effects through lower oil prices induced by increased financial stress. There is also a noticeable difference in the associated response pattern between the aggregate demand shock and financial shock, illustrating the importance of identifying the latter shock as an additional source of oil price fluctuations. Finally, a positive financial shock causes a statistically significant decline in CPI in the USA.

The findings presented above can be summarised as follows. First, we find evidence that the macroeconomic impact of oil price shocks depends on the underlying causes and that each shock is associated with a distinct response pattern, which is fully consistent with the results in the literature, notably those of Kilian (2009). Second, we advance our understanding of the relation between oil price shocks and stock prices. More specifically, we find that the impact of oil supply shock on stock prices is more persistent, whereas the net effect of the aggregate demand shock on stock price changes over time. This result is broadly in line with the recent literature, such as Ciner (2013) and Degiannakis et al. (2013), which shows that the relation between oil prices and stock prices depends on the nature and origin of oil price shocks. Finally, we find that the macroeconomic impact of the financial shock is significant and thus comparable with that of the aggregate demand shock. Moreover, we find a noticeable difference in the associated response pattern between the aggregate demand shock and financial shock, illustrating the importance of identifying the latter shock as an additional source of oil price fluctuations.

[11] The effects of the oil supply shock on output and price levels in the USA are similar to Kilian (2009).

[12] The result is consistent with the finding presented in Fig. 1, which shows that a positive financial shock causes a negative and statistically significant effect on REA.

4. Conclusion

We extend Kilian's (2009) framework to identify an exogenous shock that arises from an unexpected change in financial market conditions and examine the consequent macroeconomic impacts of oil price changes. This extension is meaningful because there is emerging evidence of the financialization of commodity markets, a phenomenon characterised by a high degree of price correlation among a broad set of commodities as well as between commodities and financial assets presumably due to the greater participation of financial investors in commodity markets.

By applying Kilian's (2009) method, we identify four types of structural shocks that cause changes in oil prices, assess the relative importance of these shocks as the source of oil price changes, and examine their macroeconomic impacts. In the first step, we identify structural shocks, including the financial shock, by estimating a VAR. The impulse response analysis shows that a positive financial shock causes a statistically significant decline in oil prices, indicating that the financial shock is a key determinant of oil prices. Moreover, the estimated variance decomposition indicates that the financial shock has a relatively high explanatory power for oil price fluctuations. In the second step, we examine the impact of underlying structural shocks on the macroeconomic indicators in five major industrial countries. The impulse response analysis indicates that the macroeconomic impact of the financial shock is significant and that the importance of financial shocks as sources of macroeconomic fluctuations is comparable with that of the aggregate demand shock. This paper also furthers the understanding of the relation between oil price shocks and stock prices by showing that the impact of the oil supply shock on stock prices is more persistent, whereas the net effect of the aggregate demand shock on stock price changes over time.

The key policy implications derived from our analysis can be summarised as follows. First, policymakers must explicitly take account of changes in global financial market conditions when analyzing the macroeconomic impacts of oil price shocks. Second, the design of a stabilisation policy in response to oil price shocks must be tailored in accordance with the underlying causes because different underlying shocks could have different macroeconomic impacts in different countries. Finally, a stabilisation policy is required to be forward-looking because the net effect of underlying shocks, such as aggregate demand shocks and financial shocks, could differ and change significantly over time.

Acknowledgements

The authors are very grateful to the editor and an anonymous referee for their helpful comments on the earlier version of the paper.

References

Aloui, C., Jammazy, R., Dhakhlaoui, I., 2008. Crude oil market shocks and stock market returns. Journal of Energy Markets 3, 69–96.
Apergis, N., Miller, S.M., 2009. Do structural oil-market shocks affect stock prices? Energy Economics 31, 569–575.
Arouri, M., Rault, C., 2012. Oil prices and stock markets in GCC countries: empirical evidence from panel analysis. International Journal of Finance and Economics 17, 242–253.
Basak, S., Pavlova, A., 2013. A Model of Financialization of Commodities. SSRN. http://ssrn.com/abstract=2201600
Basher, S.A., Haug, A.A., Sadorsky, P., 2012. Oil prices, exchange rates and emerging stock markets. Energy Economics 34, 227–240.
Buyuksahin, B., Robe, M.A., 2012. Speculators, Commodities and Cross-Market Linkages. SSRN. http://ssrn.com/abstract=1707103
Ciner, C., 2001. Energy shocks and financial markets: nonlinear linkages. Studies in Nonlinear Dynamics and Econometrics 5, 203–212.
Ciner, C., 2013. Oil and stock returns: frequency domain evidence. Journal of International Financial Markets, Institutions & Money 23, 1–11.
Cong, R.G., Wei, Y.M., Jiao, J.L., Fan, Y., 2008. Relationships between oil price shocks and stock market: an empirical analysis from China. Energy Policy 36, 3544–3553.
Cunado, J., Perez de Gracia, F., 2005. Oil prices, economic activity and inflation: evidence for some Asian countries. Quarterly Review of Economics and Finance 45, 65–83.
Davig, T., Hakkio, C., 2010. What is the effect of financial stress on economic activity. Economic Review (Q II), 35–62.
Degiannakis, S., Filis, G., Floros, C., 2013. Oil and stock returns: evidence from European industrial sector indices in a time-varying environment. Journal of International Financial Markets, Institutions & Money 26, 175–191.

Hakkio, C.S., Keeton, W.R., 2009. Financial stress: what is it, how can it be measured, and why does it matter? Federal Reserve Bank of Kansas City. Economic Review (Second Quarter) 94 (2), 5–50.
Hamilton, J.D., 1983. Oil and the macroeconomy since World War II. Journal of Political Economy 91, 228–248.
Henderson, B.J., Pearson, N.D., Wang, L., 2012. New Evidence on the Financialization of Commodity Markets. Working Paper. Georgetown University of Illinois.
Hooker, M.A., 1996. What happened to the oil price-macroeconomy relationship? Journal of Monetary Economics 38, 195–213.
Huang, R.D., Masulis, R.W., Stoll, H.R., 1996. Energy shocks and financial markets. Journal of Futures Markets 16, 1–27.
Jammazi, R., Aloui, C., 2010. Wavelet decomposition and regime shifts: assessing the effects of crude oil shocks on stock market returns. Energy Policy 38, 1415–1435.
Kang, W., Ratti, R.A., 2013. Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets, Institutions & Money 26, 305–318.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. American Economic Review 99, 1053–1069.
Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. stock market. International Economic Review 50, 1267–1287.
Kilian, L., Vega, C., 2011. Do energy prices respond to U.S. macroeconomic news? A test of the hypothesis of predetermined energy prices. Review of Economics and Statistics 93, 660–671.
MacKinnon, J.G., 2006. Bootstrap methods in econometrics. Economic Record 82, 2–18.
Morana, C., 2013. Oil price dynamics, macro-finance interactions and the role of financial speculations. Journal of Banking & Finance 37, 206–226.
Nissanke, M., 2012. Commodity market linkages in the global financial crisis: excess volatility and development impacts. Journal of Development Studies 48, 732–750.
Park, J., Ratti, R.A., 2008. Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Economics 30, 2587–2608.
Singelton, K.J., 2012. Investor Flows and the 2008 Boom/Bust in Oil Prices. Working Paper. Stanford Graduate School of Business.
Tang, K., Xiong, W., 2012. Index investing and the financialization of commodities. Financial Analysts Journal 68, 54–74.
Yoshizaki, Y., Hamori, S., 2013. On the influence of oil price shocks on economic activity, inflation, and exchange rates. International Journal of Financial Research 4, 33–41.